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Poker as a Domain of Expertise

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Abstract
Poker is a game of skill and chance involving economic decision-making under uncertainty. It is also a complex but well-defined real-world environment with a clear rule-structure. As such, poker has strong potential as a model system for studying high-stakes, high-risk expert performance. Poker has been increasingly used as a tool to study decision-making and learning, as well as emotion self-regulation. In this review, we discuss how these studies have begun to inform us about the interaction between emotions and technical skill, and how expertise develops and depends on these two factors. Expertise in poker critically requires both mastery of the technical aspects of the game, and proficiency in emotion regulation; poker thus offers a good environment for studying these skills in controlled experimental settings of high external validity. We conclude by suggesting ideas for future research on expertise, with new insights provided by poker.

Keywords
Economic decisions, probabilistic decision-making, risk, expertise, poker

Introduction
In everyday and expert settings, humans are able to cope with high levels of complexity and ambiguity. We are able to make economic decisions under time pressure, on the basis of limited information, and with various levels of risk and uncertainty associated with the outcomes. Most of the decisions are menial, such as which type of bread to buy for dinner; others are personally and professionally significant, such as whether to trade a stock at a given price. Some decisions may even be life changing, such as deciding to undergo surgery on short notice. How humans make such decisions is a foundational issue in behavioral economics, and in social and cognitive psychology. This issue is also important for research on expertise, because some decisions (such as trading stocks) are made in a manner that may be conducive to the development of expertise (involving repeated performance, explicit criteria for decision quality, competitive environment, and feedback).

Ultimately, to understand expertise in risky decision-making we need to discover what psychological mechanisms underpin both the success and failure of decisions in complex, ambiguous, and intricate real-world settings (Klein, 2008; 2015). Unfortunately, the settings of such real-world problems are generally not readily amenable to traditional experimental methods. Therefore, the cognitive underpinnings of human decisions are often investigated in highly simplified laboratory tasks, which are intended to capture some hypothetical mechanism or essential aspect of real-world problems (Buelow & Blaine, 2015; Buelow & Suhr, 2009; Kahneman & Tversky, 1979). This creates a tension: Restricted tasks abstract away much of real-world domain complexity, ambiguity, and the "world knowledge" that experts[1] bring to bear on the task. This allows one to arbitrate more definitively among competing mechanistic hypotheses, but also raises the question of whether those putative mechanisms are a factor in more realistic settings.

Laboratory tasks are meant to be analogues of real-world environments, but whether the tasks actually have relevance outside the laboratory has to be taken on faith (that is, researchers' intuition for how similar their simplified, abstract decision-making task really is to a real-world task setting). Traditional decision-making tasks are thus designed for laboratory convenience—often presented in text or numerical form using novice subjects and/or with domain-general problems. This makes them particularly limited in terms of shedding light on *skilled* decision-making processes in rich and more natural contexts.

The study of *games* has been a valuable route for cognitive scientists and can offer some middle ground between experimental control and ecological validity. Most everyday natural decisions—such as choosing ingredients for cooking a meal or deciding on what to wear to a party—cannot be given comprehensive mathematical definitions, nor are there often clear normative criteria on the goodness of a decision. However, many games are everyday tasks with definable rules that can be compactly represented. Also, gameplay offers means to design recurring situations that can be used to present decision-making tasks that have both experimental control and high ecological validity (such as choosing the next move in chess). Game decisions can, moreover, often be varied in terms of task difficulty and complexity to suit particular participants or experimental questions. Finally, mathematical analysis of games has in many cases provided normative standards whereby decision quality is evaluated.

In this review we show how these desirable characteristics apply to the game of poker, which can serve as a valuable model system for studying expert economic decision-making under risk and uncertainty. Poker is a well-structured game played in a social setting with many different game variants involving randomness and probabilistic economic decision-making. These aspects of poker make it attractive for various scientific disciplines interested in economic or rational decision-making at the individual and social levels. Poker also comes with a very large online community of players generating big datasets and powerful data-gathering opportunities (e.g., Eil & Lien, 2014; Siler, 2010) similar to many electronic sports (Esports) games (e.g., Thompson, McColeman, Stepanova, & Blair, 2017). In general, games that have gone online provide enormous research opportunities—poker in particular, given its long history of defined analytic structure, game theoretical analysis, as well as large player base.

We will argue that poker also offers a novel look into expertise, since the concept of poker skill is more complex than the much-studied *technical* skill in other well-studied game domains such as chess. This is due to the element of chance in the game: Skilled poker players need to have *emotional* tolerance of *outcome variability*—that is, to be successful they need to able to control and reflect on their negative emotions when even right choices can lead to catastrophically bad outcomes merely due to chance. Compared with chess, poker is also typically played with a larger group of people, making emotion regulation particularly important.

So far, this element of poker has not been thoroughly studied, despite the potentially significant benefits for decision- and cognitive sciences. Therefore, poker has strong, but as yet untapped, potential for research on social- and cognitive psychology, decision-making, and expert performance.

Overall, while poker has received a lot of attention outside academia[2], up until recently much of the research on poker has been *clinically* motivated; for example, evaluating how pathological gambling behavior manifests in poker, or *theoretically* focused on using poker as a testbed for artificial intelligence (see Brown & Sandholm, 2019; Moreau, Chabrol, &

Chauchard, 2016; and Rubin & Watson, 2011). We argue that games of economic decisions such as poker can and should be used more in basic behavioral research on decision-making and expertise under risk and uncertainty. The element of randomness may make mastering poker different compared to mastering many deterministic games—however, as articulated by Siler (2011), it is precisely this stochastic nature of poker that makes it a much more realistic task environment reflecting the vagaries and uncertainties of many real-life phenomena such as financial decisions.

In our review we first provide a section describing the technical aspects of poker and explain the basic structures of the game and how the element of chance influences skill development. Then we address the following review research questions (RQs): (1) *What are the components of poker skill?* We describe how the concept of poker skill comprises both *technical* (mathematical, statistical and game theoretical) and *emotion regulation* ("mental game") components, and how various social elements of the game can bias players' decision-making. (2) *How do poker skills develop into expertise, and how does poker allow study of expertise*? We link the components and development of poker skill to previous work on *expertise*, *deliberate practice*, and *skilled intuition* and show that poker offers a novel way to look at expertise and expert performance due to its emotion regulatory skill aspects. (3) *How can future studies on expertise and decision-making make use of poker?* We conclude our review by detailing how future studies can draw insights from poker to examine skilled decision-making under emotional and social constraints.

Table 1 illustrates the features of poker reviewed in this paper and their relevance to research on expertise and decision-making.

Table 1: Features of poker and their relevance for decision-making and expertise researchers

Poker Feature	Research Relevance; Poker allows study of the following:
Incomplete information	Microcosm of *naturalistic* financial decision-making
Interplay of skill and chance	Skill perception and biases in decision-making: in the short term, bad players may win (inflated skill perception), and good players may lose (obfuscation of true skill)
Male-dominated social environment	Masculinity and gender stereotypes in a competitive setting, gender biased decision-making
Technical and emotional aspects of skill	Interplay between emotion regulation ability and decision-making accuracy
Multiple sources of both public and private information	"Game theory optimization" strategies, how skilled players avoid exploitation
Skilled intuition	Ecologically valid skilled intuition in a "medium validity" (as opposed to "high validity"; e.g., chess) environment

Basic Properties of Poker

In every poker variant the winnings of one player are the losses of another (poker is a *zero-sum* game; Wright, 2001). Decisions in poker are economic decisions made in partially unpredictable environments with potentially undesirable outcomes (it is a game of *randomness* and *risk*). Players have to decide between various options and act without seeing the other players' cards (it is a game of *incomplete information* (Sklansky & Malmuth, 1999). Players must also adapt to changes in the nature of game information across the phases of the game, and, according to Salen and Zimmerman (2004, p. 149) poker contains several *types of information*. Furthermore, while the game is turn based, the pace of game play between human opponents still often creates substantial *time pressure*[3]. The time used for deliberation can also indirectly disclose information on one's strategy, further pressuring players to control their behavior. Poker is also a *dynamic* environment, as the "game state" changes even when the agent does nothing. The social pressure and the monetary stakes involved create additional cognitive and emotional load—for professional players the rewards can reach millions of US dollars.

In the technical examples that follow, we will focus on the most popular variant of poker called *No Limit Texas Hold'Em* (NLHE). In NLHE, each player is first dealt two cards, and the goal is to form the best five-card combination from one's own two cards (not seen by the other players) plus cards dealt on the table (shared with all other players). There are up to four rounds of betting, during which the number of publicly shared cards increases, starting with no shared cards and ending with, at most, five. Between each round the players can make investment decisions on whether to keep playing, how much to invest in the pot, or give up (i.e., fold)[4]. The pot will go to the winner (or split between winners in case of ties), who is the player with the best card combination, or the only one not to have folded.

Skill and Chance

Generally, poker is viewed as a game of both skill and chance, but the extent to which one or the other dominates is debated (Croson, Fishman, & Pope, 2008; Dedonno & Detterman, 2008; Fiedler & Rock, 2009; Levitt & Miles, 2014; Meyer, von Meduna, & Brosowski, 2013). Anecdotal evidence supports the view of poker as a game where one's skills can constantly be improved (Brunson, 2005; Sklansky & Malmuth, 1999; Tendler, 2011). The consensus view in academic discussion is that although chance plays a role in *short-term* results, with enough skill poker can be played profitably *in the long run*. Empirical support for this view comes from an analysis of 456 million online poker hands (van Loon, van den Assem, & van Dolder, 2015). Van Loon et al. (2015) created a simulation based on these data, comparing the best players with the worst ones, and found that skill starts to dominate chance when performance is assessed over about 1,500 or more hands of play (see Fiedler & Rock, 2009, for similar results). Skill has a demonstrably significant role also in real-world poker success. Professional players are consistently more successful than amateurs at the World Series of Poker (Croson et al., 2008; Levitt & Miles, 2014).

One way to illustrate the role of chance in poker is through simulations of *outcome variability*. Players' levels of skill are reflected in their *win rate*, which is the average amount of profit over some number of played hands (usually 100; van Loon et al., 2015). The standard deviation of a player's win rate (a measure of outcome variability) can be 20 times higher than the win rate itself (Billingham et al., 2013). To illustrate, we will compare two equally skilled hypothetical players playing 200,000 hands each. By assuming both players have somewhat low win rates (on the statistical edge of making long-term profit), we might observe the situation presented in Figure 1: One player could be winning substantially (> 15 000 €), and the other clearly losing (-5000 €). Outcome variability is thus a highly significant factor, masking a player's "true" skill as defined by the expected long-run winnings (dashed line in Figure 1). This means that while poker differs from games of pure chance (such as roulette) or games of skill and chance where long-term profit is unattainable (e.g., blackjack; Bjerg, 2010), outcome variability still makes it challenging to empirically estimate the actual skill level of any individual player from naturalistic play data[5].

However, player skill can also be estimated experimentally, by using *representative decision-making tasks,* with known normative solutions: more (technically) skilled players should consistently reach that solution more quickly and/or reliably. In two laboratory studies (Linnet et al., 2010; 2012), those who had played poker at least once a week for at least a year were better at estimating betting outcomes than less experienced ones. Two online studies with simplified poker tasks showed that the amount of poker experience was strongly and positively associated with making mathematically appropriate poker decisions (Laakasuo, Palomäki, & Salmela, 2015; Palomäki, Laakasuo, & Salmela, 2013a). Thus, components of poker skill can be isolated and studied both "in the wild" and in the laboratory.

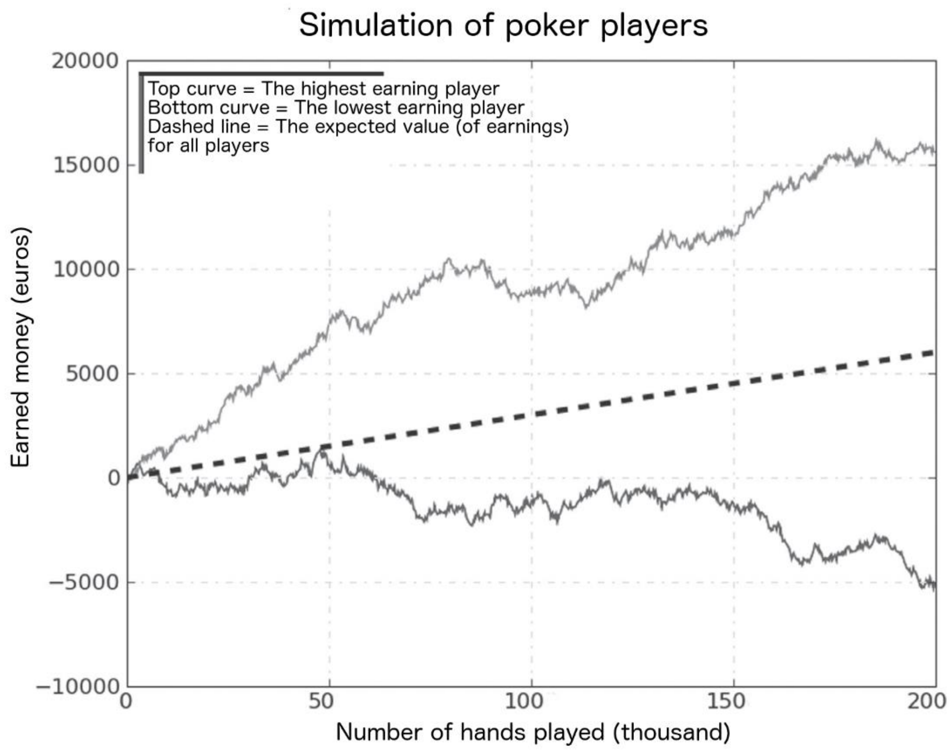

Figure 1. A simulation of 900 NLHE "poker players" with equal win rates. Win rates are based on "big blinds"'; that is, the minimum bet size allowed by the rules. These win rates are calculated based on 3 big blinds—in this case, euros—per 100 hands played, with a standard deviation (*SD*) of 80 for the win rates (typical win rate *SD*s in NLHE are 70-90; Billingham et al., 2013). Note that the "players" are simulated processes based on two parameters (win rate and $SD_{\text{win rate}}$) and thus independent of one another. The figure depicts only the highest and lowest earning players (top and bottom curve, respectively), and the expected value of earnings for all 900 players (dashed line). (Translated into English from Laakasuo, Palomäki, & Lappi, 2015).

Components of Poker Skill (RQ1)

In this section we address our first research question on the components of poker skill. We consider what is required of a good poker player; that is, someone who is generally able to make a long-term profit by playing poker. We propose a division of poker skill into *technical* and *emotion regulatory* (sub)skills.

Technical poker skills refer to in-depth knowledge of game mechanics and betting strategies, and how to apply them to increase one's chances of winning. In poker, technical skills alone are not enough for long-term success if dysfunctional emotional responses systematically impair players' decision-making. Ample evidence shows that emotions have a significant impact on success in poker, and emotion regulation skills are necessary to play poker consistently at a high level. Below, we explain how acquiring mastery of poker involves not only technical and strategic knowledge of the game but also an aspect of "mind management" or mental game ability.

Technical Skills

In terms of technical skill elements, Billings and colleagues (2002) have proposed that in order to play poker, one needs to understand at least the following concepts: (1) *hand strength and hand potential*, *(2*) *betting strategy, bluffing, unpredictability*, and (3) *opponent modeling.* Palomäki et al. (2013a), among others, have suggested that (4) *bankroll management* is also vitally important. These four key elements are explained below.

Hand strength and hand potential refer to how strong a player's hand currently is and the probability of a given hand strength changing—

relative to the opponents' assumed hand strengths—as further cards are dealt (see the Appendix for detailed examples). Calculations of hand strength and hand potential require knowledge of poker betting odds in a given situation, mathematical aptitude, and working memory capacity (e.g., DeDonno, 2016; Meinz et al., 2012).

Betting strategy, bluffing, and unpredictability refer to knowledge of when and how much to bet or raise (or fold) in a sufficiently unpredictable manner to maximize one's profit and protect oneself from exploitation. Betting strategy refers for instance to the decision to bluff with a fixed frequency or not, as a player might decide *a priori* to bluff a given number of times in a game. These skill elements require players to apply (either explicitly or implicitly) the concepts of game theory, such as *Nash equilibrium*[6], in their own decision-making.

Opponent modeling refers to estimating the full range of an opponent's possible hands. Specifically, opponent modeling relates to how various behavioral and social opponent characteristics, such as betting patterns, physical "tells", or gender, influence the way (or what range of possible hands) one's opponents are predicted to play—and, consequently, how they should be played against to maximize profit. This generally requires interpreting concealed social signals, reading covert facial expressions, and detecting deception in general.

Bankroll management is the knowledge of how much money is needed for playing, in relation to the stakes played, to avoid going broke. That is, how much capital is needed to withstand outcome variance and avoid "going broke due to merely bad luck." Good bankroll management skills are typically associated with a good understanding of the concepts of statistical variance and risk of ruin (Browne, 1989; Palomäki et al., 2013a).

The depth of the technical aspects of poker is evidenced by clear differences in technical skill between proficient and novice poker players. For example, in a laboratory experiment St. Germain and Tenenbaum (2011) compared the performance of proficient players, with significant tournament success, to intermediate and novice poker players in a simulated poker task during which participants had to "think out loud." Proficient players outperformed both intermediate and novice players (in terms of profit), and self-reported the highest amount of thought processing and attention to relevant technical aspects of the task—such as betting patterns, estimated opponent ability, future opponent actions and "tells," and hand selection and strength. Practicing these skill elements leads to better performance: DeDonno and Detterman (2008) conducted a laboratory experiment where naïve poker players systematically practiced technical poker concepts which lead to improved success in the game. The players were given information and feedback about (1) when and why to pay attention to the other players' decisions; (2) the concept of playing fewer hands, and how to play them; and (3) hand ranking strategy with quality values for the initial hand. These correspond to opponent modeling, betting strategy, and evaluating hand strength and hand potential, respectively.

Poker is a knowledge-rich domain, with complex demands on both technical and strategic skills. These demands present information processing challenges requiring the player to go beyond the information embodied in the cards and explicit in the rules. We have provided a detailed poker task analysis in the Appendix, which illustrates the complexities involved in poker decision-making.

Poker is also well-suited to facilitate study of players' information processing because the relationship between different forms of information is relatively clear and understood. The above aspects of technical poker skill embody different challenges of *information manipulation* (Salen & Zimmerman, 2004, p. 148), in the sense of the information embodied by the cards as defined by the rules of poker. This information can take multiple forms, including: (1) *Information known to all players*; i.e., the five "community cards" shown on the table; (2) *Information known to only one player*; i.e. the two "hole" cards of each player; (3) *Information known to the game only*; e.g., the unused cards in the deck; and (4) *Randomly* *generated information*; i.e., the shuffling of the deck. Part of the technical skill in poker is to know which form of information the game embodies at any given time—and to keep track of and predict how the game's information moves between these forms.

For example, a certain amount of the information known only to one player (the hole cards), can be leaked to other players due to that player's response to the *turn*, *flop*, or *river* (see the Appendix for explanation of these terms). In fact, in a recent study, Frey, Albino, and Williams (2018) analyzed 1.75 million poker hands and found that winning (skilled) poker players were better than losing (unskilled) players at *integrative* information processing—creating new information based on the interaction between their own hole cards and their opponents' betting patterns. This made the winning players' decision-making less exploitable and harder for others to reverse engineer (Frey et al., 2018).

To recap, technical poker skills consist of knowledge of hand strength and hand potential, betting and bluffing strategy, ability to avoid exploitation (playing unpredictably) and to exploit others, and bankroll management; all of which can be viewed in terms of challenges for information manipulation. However, we note that empirical research on technical poker skill development in terms of information manipulation strategies is still relatively scarce.

Emotion Regulation Skills

Due to statistical variance in the game, even technically skilled poker players regularly encounter losing streaks and "bad beats" —losing money in situations where losing is objectively unlikely, and not the result of normatively poor decision-making. Losing large sums of money often elicits negative emotions, which, in turn, can have detrimental effects on upcoming decisions. For example, in a bout of anger an experienced and otherwise technically skilled player might forgo sound betting or bankroll-management strategies, ending up playing with too high stakes and betting erratically despite *factually* knowing it is mathematically inadvisable. Thus, in addition to technical skill elements, the concept of poker skill encompasses an *emotion regulatory* aspect. Emotion regulation skills refer to the ability to withstand the arduous, yet inevitable, losing streaks without having them affect the quality of one's decisions (Boujou et al., 2013; Palomäki et al., 2013a). These skills may be conscious processes explicitly controlling one's impulses by willpower or positive self-talk, or they could be more unconscious processes, which might be termed trait emotional stability or "character" developed by surviving previous encounters.

McCormack and Griffiths (2012) interviewed professional and recreational poker players and found that professional players were not only more likely to be logical and controlled in their behavior, but also took fewer risks and were less likely to chase after losses (i.e., keep playing in an attempt to win back their losses). Conversely, recreational players showed more signs of losing control, taking unnecessary risks and playing under the influence of intoxicants. In correlational online studies, poker experience has been found to be negatively associated with the psychological traits of *emotionality* (Laakasuo, Palomäki, & Salmela, 2014), *self-rumination* (Laakasuo, Palomäki, & Salmela, 2016; Palomäki et al., 2013a) and emotional *sensitivity to losses* (Laakasuo et al., 2016; Palomäki et al., 2014). Experienced players are thus less emotional, dwell less on negative thoughts, and report higher emotional tolerance of poker losses than do inexperienced players.

Moreover, Palomäki and colleagues (2013a) report that in an online setting with simplified poker tasks, experienced players—but not inexperienced—made mathematically better poker decisions when they had a strong tendency for *self-reflection*. Self-reflection is a trait related to analyzing one's past mistakes in a cool and detached manner. Consistent with these results, Leonard and Williams (2015) employed a measure of technical poker skills and betting strategy and found that proficient players were less susceptible to gambling fallacies and had higher emotional tolerance for financial risk and better social information processing skills.

Tilt: Intense Moral Anger Revealed in Poker

The importance of emotion regulation skills and aversion to loss (via pursuing risk) in poker is underscored by the phenomenon known as *tilting*, which refers to losing control due to negative emotions—typically related to bad beats or prolonged losing streaks—and making strategically weak decisions and losing significantly more money than otherwise (Palomäki et al., 2014; Moreau, Delieuvin, Chabrol, & Chauchard, 2017). Extreme cases of tilting have even led to losing entire life savings within minutes, and to self-reported memory losses of the preceding events (Palomäki et al., 2013b; Tendler, 2011).

Poker communities seem to agree that tilting is a significant phenomenon: in an online study, 88% of poker players reported having tilted severely at least once within their last 6 months, 43% more than five times, and 24% more than 10 times (Palomäki et al., 2014). Hence, this form of "mental disarray" occurs with a substantial frequency, leading to substantial costs for those involved. These findings are in line with the studies by Smith, Levere, and Kurtzman (2009), as well as by Eil and Lien (2014), who used big data on millions of played online poker hands and found that players tend to pursue risk when losing, but play cautiously when winning. This effect is possibly driven by emotional aversion to loss.

Social cues may also interact with emotional reactions during poker decision-making: In an online experiment employing a poker decision-making task with mathematically defined optimal choices, inducing the feeling of anger (via reading emotional stories) reduced decision-making accuracy. However, this effect was driven by a social cue: displaying a pair of human eyes that "followed" the participants' mouse cursor during the task (Laakasuo, Palomäki, & Salmela, 2015).

What leads to such costly lapses in judgment? In a qualitative study on poker players' experiences of losing significant amounts of money, tilting was characterized by feelings of anger, frustration, and significantly, injustice (Palomäki et al., 2013b; see also Barrault et al., 2014). Social elements such as unfriendly comments by other players often fuel the negative emotional states leading to tilting (Browne, 1989). The sense of *injustice* is particularly interesting, as it makes tilting a form of moral emotion: Individuals (sampled in Palomäki et al., 2013b) who tilt reported feeling personally insulted, and that they "unfairly" lost money for which that had worked diligently. They viewed variance as "bad luck," took it personally, and started pouring their earnings into the game and chasing their "fair chance." The authors postulated (Palomäki et al., 2013b) that the psychology of tilting could be viewed as *moral anger*: Losing due to bad luck is perceived as "cosmically" unjust, which motivates an overly aggressive yet ineffective retaliation strategy of excessive betting. In the aftermath of tilting, the players reported being disappointed in themselves and that they were ruminating over lost resources.

Experienced players, however, differ from inexperienced ones in their reporting of better skills for regulating negative game-induced emotions. Some experienced players in (Palomäki et al., 2013b) reported that their general emotion regulation skills had improved through playing poker. These players also thought that a clear understanding of mathematical concepts, such as variance, is related to a mature disposition towards encountering "bad luck" (*"luck doesn't exist, only variance does"* [Palomäki et al., 2013b]), which suggests that in poker, emotion regulation skills and technical skills are tightly intertwined.

Social Nature of the Game

In poker, the dynamics of social interaction—such as opponent characteristics or gender effects—are crucial in understanding decision-making quality. The social setting of the game also plays a significant role in biasing poker decisions on the one hand, and on the other provides players with potentially accurate information in the form of behavioral "tells" (Caro, 2003).

Schlicht, Shimojo, Camerer, Battaglia, & Nakayama (2010) employed a simplified poker task and found that opponents whose facial expressions displayed more trust were more often folded (given up) against. The authors argued that by betting the opponent is implicitly "sending a message" that he has a strong hand, and, because he looks trustworthy, the message is believed. In another study with a poker task involving repeated decisions against the same opponent, participants' decisions were more strongly influenced by their opponents' prior actions when the opponents were represented as humans rather than as computers (Carter et al., 2012).

In both of these studies, the human opponents were presented as males. Poker players seeking long-term engagement with the game value masculine identities and player traits (Wolkomir, 2012), and the vast majority (90-95%) of poker players are male (Palomäki et al., 2014; see also Abarbanel & Bernhard, 2012). Also, poker decision-making itself seems to be gender-biased: In an experiment using realistic online poker tasks where opponents were represented as either male or female avatars, participants (of whom 93% were male) bluffed 6% more frequently at online tables with female-only avatars compared with male-only tables amounting to a significant difference over time (Palomäki et al., 2016). A majority of the participants also reported that the gender of their opponents did not influence their decisions to bluff, which suggests an implicit (unconscious) bias in bluffing female opponents, who might have been perceived as "easier" targets than males.

Together, these results highlight the notion that the social nature of poker is a key element in fully understanding decision-making quality and biases in the game. But turning it around, poker is a tool to study decision-making and socially driven decisions in a market environment-like scenario, which, to date, has received relatively little attention in research.

Measuring Poker Skill

Time, speed, or distance measures can be used in many sports for objective quantification of performance; and in chess—the game most studied in cognitive science—Elo points provide a high-validity measure of performance. In poker, however, skill-level is often assessed indirectly by self-reported experience or simplified poker tasks, as previously discussed. The element of chance obfuscates empirical assessment based on earnings and calls for very long observational histories. It would be better if the probabilistic "goodness" of individual players' decisions (e.g., the expected value in terms of monetary winnings) could be evaluated based on a reasonable number of hands played.

The expected value of poker decisions can be evaluated in simplified scenarios (see Laakasuo, Palomäki, & Salmela, 2015; Leonard & Williams, 2015). However, evaluating the expected value of complex poker decisions "in the wild" is extremely difficult, given all the aforementioned cues potentially affecting (or biasing) the players' decisions and the element of chance. One way to tackle this problem is by benchmarking poker players' decisions against the best artificial intelligence (AI) poker programs. Somewhat recently, an NLHE AI not only won the 2016 Annual Computer Poker Competition, but in 2017 defeated four highly skilled professional poker players in heads-up (one versus one) matches for about $1.8 million over 120 thousand hands[7]. Poker AI has thus been benchmarked against the highest human standard and proven sophisticated enough to beat the very highest-performing human players. Therefore, these programs can act as a normative reference whereby the performance of sub-elite players at least can be evaluated. This would be based on how well their decisions correspond to the consensual decisions of the best AI. To our knowledge, such efforts have not been made yet, highlighting a potential avenue for future research.

Development of Poker Expertise (RQ2)

Our second research question asked how poker skills develop into expertise and how poker allows for studying expertise. The complexity of requisite technical knowledge in poker (as explained in "Technical Skills," above) is evident even in a simplified poker decision-making task, which we have provided in the Appendix. Poker also lends itself well to be examined under theories of *expertise*. Due to having a chance component embedded in a well-defined rule structure, poker even helps extend existing work on expertise to domains where decision quality is not fully correlated with observed outcomes (unlike in chess, for example, where consistently making the best decisions reliably leads to good outcomes).

Deliberate Practice

The *deliberate practice* (DP) framework is the most established explanation for how expertise is acquired (Ericsson, 2007; Kaufman & Duckworth, 2017). It can be applied to study the development and acquisition of poker skill, expertise, and skilled intuition. In turn, the special features of poker relating to chance, emotion regulation, and social factors show that acquiring mastery of only the technical aspects of the game does not guarantee long-term success. So far, the DP framework has been used mainly in relation to what we have called technical skill, and therefore we suggest that the question of emotion regulatory skill development (through DP or otherwise) is an important new direction.

Within the DP framework, research on the cognitive foundations of expertise has shown that the superior performance of experts is not based on general intelligence, but on a vast amount of well-organized topic related knowledge (Ericsson, Krampe, & Tesch-Römer, 1993; Ericsson & Lehmann, 1996; Ericsson & Williams, 2007; Kaufman & Duckworth, 2017). This knowledge is clearly acquired through experience, and the DP framework characterizes the nature of that experience by making one core assumption: An individual's level of performance in the domain is monotonically related to the amount of a specific type of practice (DP) that person has engaged in. Put differently, the attained level of expertise and performance are a function of the time invested in DP. In music training DP refers to (typically solitary) practice to improve specific technical or artistic aspects of one's skill, but not studying music theory, public performances, or "jamming" (Ericsson, Krampe, & Tesch-Römer, 1993). In chess, studying and determining the best moves in mid-game[8] would count as DP, while merely playing or spending time on studying the literature generally would not. According to Ericsson (2016), as a predictor of performance, accumulated DP is more important than the amount of overall domain experience, general intelligence, or innate domain specific talent *combined* (for further discussion, see Ackerman, 2014; Macnamara, Hambrick, & Oswald, 2014; Macnamara, Moreau, & Hambrick, 2016; and Hambrick et al., 2014).

Technical Poker Skill Acquisition via Deliberate Practice

Although poker does not have a formal teaching culture like in classical music and professional sports, the range of self-coaching strategies suggests that the online poker sub-culture is a mature culture of expertise. A common recommendation for "serious" novice players seeking to improve their skills is to use poker analysis software, which allows for monitoring of session-by-session statistics on profit or loss and betting strategy (Billingham et al., 2013). After each session, the players can then carefully analyze how they played and what they could have done differently. Poker players actively interact over virtual communities to scrutinize poker strategy. Skilled players, in particular, frequently post detailed breakdowns of how they played for general discussion (O'Leary & Carroll, 2013). Their aim is to fine-tune their mathematically informed strategic decisions in poker (Parke & Griffiths, 2011).

We posit that in poker, this type of *study of betting strategies* in specific game situations would count as DP for technical skills (we are not aware of specific practice forms that would be geared toward emotion regularity skills, that is, DP for non-technical skills, in poker). Although this is not solitary practice designated by a teacher, the explicit *goal* of improving specific skills and the setting-up of clear *feedback* mean the process can be viewed as DP, in the context of poker.

Moreover, posting one's poker hands (breakdown of a string of decisions within a specific hand) for analysis and scrutiny on online poker forums has three characteristics of DP. First, a clear task structure, wherein the players often receive step-by-step walk-throughs on why certain decisions should or should not be made. Such walk-throughs may also *isolate subtasks*, such as focusing on different stages of the hand (e.g., decisions on the flop, turn, or river). Second, there should be clear goals for the players who *aim for self-improvement*. For example, the feedback generated by playing the game might be positive for bad decisions (winning money despite making a decision with negative expected value), but posting such situations online for scrutiny helps players discover the actual goodness of their decisions. The proximal goal for players who seek feedback on their decisions is often not merely to enjoy poker or winning since they also post hands where they have *won* but are uncertain whether they played correctly[9]. Finally, there is the element of diligent *repetition*, as players who strive to get better keep posting poker hands for scrutiny, which, in turn, helps them increase their skills.

It should also be noted that because poker is a competitive game, skilled players might have an incentive *not* to help novice players to improve—or even an incentive to hinder their progress. Novice players aspiring to get better thus sometimes need to discern between misleading and accurate information disseminated in online poker forums (Talberg, 2019), as aspect of social skill learning.

Emotion Regulation Skill Acquisition

The consensus is that technical poker skills can be learned via practicing and studying the game. However, studying poker alone is probably not enough to learn and improve one's emotion regulation skills, because it is not easy to "simulate in training" the loss of significant amounts of money.

Traits such as low emotionality and low tendency to self-ruminate are largely (possibly innate) predispositions that enable some people to become good players; namely, those who can endure the stressful learning period as well as the unavoidable losing streaks. Personality, IQ, and other psychological traits, when measured with standard psychometric instruments, are to a large extent stable across time, and may be difficult to alter systematically through practice. However, the malleability of such traits, and the directions of causality between poker skill development and various psychological characteristics could be fully evaluated only by employing a longitudinal study design, where poker players' behavior is measured over extended periods of time. To our knowledge, no such study currently exists and would thus offer a fruitful line for future research.

There is, however, a rich corpus of poker self-coaching textbooks that focus on improving one's mental game skills. The authors of these books typically recognize emotion control as a highly significant element in poker skill development (e.g., Angelo, 2007; Taylor & Hilger, 2007; Tendler, 2011). Similar anecdotal evidence has emerged from Esports, where professional teams and individual players have been significantly more successful in tournaments after hiring sports psychologists specializing in tilt-management (theScore esports, 2019).

Tendler (2011) draws from his experience as a clinical psychologist working extensively with poker players and offers detailed guidelines and techniques for players to improve their tilt control. He views poor tilt control in poker as an issue of consistency in individual performance level. Players perform better on some days than on others—and the overall distribution of performance level forms a bell curve around the average performance level for each player. For players with poor tilt control, this distribution is wide, reflecting a large difference in performance level between their best and worst possible performance. Players with proficient tilt control, in turn, have narrower performance level distributions. In other words, their performance is more *constant across time*—they play almost as well on their "worst day" as they do on their "best day."

It is important to note that we do not claim emotion regulation is an important "sub-skill" *only* in the game of poker. It probably has wide relevance across a range of domains, especially those dealing with risk and uncertainty. We are, however, proposing that the role of emotion regulation becomes more pronounced in poker than most domains that have been used in cognitive science to study the nature and development of *expertise*. In other fields such as

given the community cards and the Opponent's betting actions previously (and body language in live poker; or chat comments in online poker, and so on).

In the situation outlined in Figure A.1, you can estimate how "strong" your own five-card hand is against the "average strength" of the Opponent's hand range. This estimation is sometimes done quickly and implicitly, because time pressure alone often prevents explicit detailed calculations – skilled players sometimes play on multiple tables online, some on as many as 24 at a time (e.g., Rhodes, 2010).

The analysis above is an oversimplification, and merely illustrates the complexities in poker decision-making. You as a player in the game should also consider *bluffing* on the river, if your hand does not improve. Also, you could decide to *bet* initially, or *raise* the Opponent's initial bet after checking. These would entail new probabilistic dependencies, which we have omitted. While this task analysis is hypothetical, it is an empirical question how explicitly analytical (or intuitive) players' cognitive processes are in similar situations. Determining opponents' hand ranges in various situations *is* discussed across poker communities (O'Leary & Carroll, 2013).

Figure A.1. An online NLHE table (adapted from Palomäki et al., 2016). A: Opponents 1, 3 and 4 have folded (given up) and are no longer contesting the pot. B: The total amount currently in the pot, which represents all the money that has been previously waged during the current hand. C: The amount of money the player has remaining in their stack, which represent the total amount they will be able to wage during any particular hand. D: The "hole cards" of the Player, not visible to the opponents. E: The "hole cards" of the remaining opponent. F-H: The "community cards" shared by the player and the opponent. F: The flop (three first "community" cards). G: The turn (the fourth community card). H: The river (the fifth and last community card to be dealt, at this point unknown).